

RMetS special interest group meeting: high resolution data assimilation

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1 RMetS Special Interest Group Meeting: High
2 resolution data assimilation

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10 Data assimilation (DA) systems are evolving to meet the demands of convection-
11 permitting models in the field of weather forecasting. A special interest group
12 meeting of the Royal Meteorological Society brought together UK researchers
13 looking at different aspects of the data assimilation problem at high resolution,
14 from theory to applications, and researchers creating our future high resolu-
15 tion observational networks. The meeting was chaired by Dr Sarah Dance of
16 the University of Reading and Dr Cristina Charlton-Perez from the MetOf-
17 fice@Reading.

18 The purpose of the meeting was to help define the current state of high reso-
19 lution data assimilation in the UK. The workshop assembled three main types of
20 scientist: observational network specialists, operational numerical weather pre-
21 diction researchers and those developing the fundamental mathematical theory
22 behind data assimilation and the underlying models. These three working areas
23 are intrinsically linked; therefore, a holistic view must be taken when discussing
24 the potential to make advances in high resolution data assimilation.

25 **1 Background**

26 In 2003, a workshop was convened to assess the feasibility of a mesoscale now-
27 casting system [Dabberdt et al., 2005]. At that meeting the scientific challenges
28 facing high resolution precipitation forecasting were identified as improving the
29 simulation of convective processes within numerical models, improving knowl-
30 edge of convective downdrafts and gusts from individual storms and improving
31 the understanding of the initialisation of convection [Wilson and Roberts, 2006].
32 On the lack of high resolution three-dimensional observations of state variables

1 above the boundary layer, they noted there was “currently no observational
2 capability to fill this gap” [Dabberdt et al., 2005].

3 Around the same time, review articles were released summarising the state
4 of high resolution DA [Dance, 2004; Sun, 2005; Park and Županski, 2003]. In
5 all references the main problem addressed is the forecasting of precipitation at
6 fine space and time discretisations.

7 **2 Current state of data assimilation and fore-** 8 **casting at high resolutions**

9 At the present time, pressing issues with DA methods related to both the high
10 spatial and time resolution in the forecasting system are no longer limited to
11 precipitation forecasting. Issues discussed at this meeting could be grouped into
12 the following themes:

- 13 • lateral boundary conditions for nested models,
- 14 • nonlinearity of the models,
- 15 • scale disparities,
- 16 • background, model and observational errors and
- 17 • computational demands of DA at scales relevant to precipitation forecast-
18 ing.

19 Ad hoc networks of devices such as smart phones and vehicles have exploded
20 in size and functionality. These networks are currently being considered for
21 their feasibility to provide information to assimilate into meteorological models
22 [Mahoney and O’Sullivan, 2013]. These networks have the potential to provide
23 surface measurements at the resolutions required by future high resolution data
24 assimilation systems, however they will still lack the three-dimensional structure
25 desired to fill the aforementioned observation gap.

26 Numerical weather prediction has benefited greatly from an increase in avail-
27 able computational power. This has allowed the models to grow rapidly in com-
28 plexity and resolution, producing much more realistic simulations. Likewise the
29 number, type and quality of observations have increased, thanks to the expan-
30 sion of radar networks and increases in the number and quality of satellite data
31 products. However, the data assimilation techniques to combine these two areas
32 of science in order to initialise a forecast are not yet capable of utilising all the
33 modern advances in modelling and observation. As an example, only around 5%
34 of scatterometer data are assimilated into both global and limited area models
35 at the MetOffice, whereas in the global model only 24% of AMDARS data is
36 assimilated which increases to 68% in the high resolution model [personal com-
37 munication, MetOffice]. The reasons for the number of observations utilised in
38 models of different resolution are complicated and vary greatly by observation

1 type. In some cases it is due to the resolution of the observations, their tempo-
2 ral and physical spacing or the quality control procedures used. Hence impact
3 studies of potential new observations are proving necessary to quantify the ben-
4 efits of additions to observing networks [Eyre and Weston, 2013; Simonin et al.,
5 2013a].

6 In the summer of 2012 during the London Olympic Games, the MetOffice
7 demonstrated its numerical weather prediction (NWP) based nowcasting sys-
8 tem using 4D-Var [Golding et al., 2013; Simonin et al., 2013b]. Nowcasts are
9 very short-range, high resolution forecasts used to give a prompt, quantitative
10 forecast of hazardous weather and precipitation. This was an advance on previ-
11 ous nowcasting systems which used extrapolation and heuristic techniques, and
12 is described in Sun et al. [2013].

13 **3 Scientific presentations**

14 Dr Ali Rudd of the University of Reading began the presentations by talking
15 on the subject of model errors in high resolution, hence convection-permitting,
16 numerical weather prediction models. A random parameter perturbed physics
17 scheme has been used to represent the uncertainties due to model error in a
18 convective-scale research ensemble prediction system (1.5km-EPS). As a test
19 case, they used a DIAMET [DIAMET, 2013] flight campaign case, during which
20 measurements were made of a frontal wave with structures not captured by the
21 Met Office UKV (1.5km) operational model forecast or the 1.5km-EPS control
22 forecast. The random parameters scheme had the effect of changing the spread
23 of the ensemble, but did not improve the forecast skill in capturing the banding
24 observed (by radar) in the rainfall [Baker et al., 2014]. It is vital to understand
25 these changes in ensemble spread in order to tune an ensemble data assimilation
26 system such as the ensemble transform Kalman filter that was used.

27 Prof Rob Scheichl of the University of Bath spoke on multilevel approaches
28 from numerical analysis which show great potential in the next generation of
29 data assimilation applications. These included geometric multigrid methods for
30 the fast solution of a linear system [Buckeridge and Scheichl, 2010] where the
31 matrix in question is the background error covariance matrix from variational
32 data assimilation. Techniques from multilevel methods for the efficient solution
33 of stochastic PDEs were presented [Teckentrup et al., 2013] because they promise
34 to improve the efficiency of particle filters.

35 Prof Slobodan Djordjevic of the University of Exeter spoke on high resolution
36 modelling of urban flooding events [Chen et al., 2012a,b]. With satellite imagery
37 used to generate a topological network of the area in question, a multi-layered
38 approach to calculation of flood extents was shown to be close to a much more
39 computationally expensive high resolution model. Case studies shown included
40 flooding events on the Isle of Wight and in Dhaka, Bangladesh. These compu-
41 tational techniques can be used to inform drainage system re-design, emergency
42 flooding evacuation plans and the health impacts of pollution. The feasibil-
43 ity of creating a real-time flood warning system in which satellite and in-situ

1 observations would be assimilated into such models was discussed.

2 Dr Lee Hawkness-Smith from the MetOffice@Reading Data Assimilation
3 Group presented work on the assimilation of radar reflectivity in high resolution
4 numerical weather prediction [Hawkness-Smith and Ballard, 2013]. Reflectivi-
5 ties were assimilated using 4D-Var into the Met Office Nowcasting Demonstra-
6 tion Project model, an NWP-based nowcasting research system.

7 Dr John Lees-Miller of the University of Bristol spoke on extracting infor-
8 mation from wireless networks for traffic modelling [Lees-Miller et al., 2013].
9 Making use of Bluetooth devices found in mobile phones and those increasingly
10 built into motor vehicles, observations of traffic densities and speeds were used to
11 build a hidden Markov model for traffic flow. These novel observations brought
12 with them a number of challenges, including privacy considerations, missed de-
13 tections and difficulties in discerning what is being measured; for example, is
14 the device which is detected actually in a car or on a bicycle? One application
15 of the model is measuring whether traffic policy changes have made an impact
16 on the dynamics of the road network. The use of such observations as described
17 by Dr Lees-Miller shows promise as a way in which to provide high resolution
18 surface observations for use in NWP models.

19 Dr Barbara Brooks from the University of Leeds was the final speaker of
20 the meeting and presented work on improving NWP forecasts by the use of
21 remotely controlled aircraft measurements [Jonassen et al., 2012]. Unmanned
22 aerial systems (UASs) are being developed to reduce costs and increase both
23 spatial and temporal resolution of the observation network in areas that are
24 currently under-observed. The main application of a particular UAS was to act
25 as a reusable radiosonde. A range of available UASs was described in order to
26 highlight the wide range of measurements that can be made using these modern,
27 reusable devices.

28 4 Discussion

29 A well-attended discussion session followed the presentations to consider the
30 future of high resolution data assimilation. Techniques to adaptively improve
31 the representation of background error covariances are already being employed
32 in high resolution DA systems [Piccolo and Cullen, 2012; Browne et al., 2014].
33 These methods go some way to addressing scale disparities in nested models,
34 particularly those disparities which can impact the simulation of boundary layer
35 dynamics. However, it was generally agreed that due to the nested nature of
36 high resolution meteorological data assimilation systems, a considerable amount
37 of the larger forecast errors on the high resolution grid come from large-scale
38 or synoptic uncertainties. During the discussion, a number of open research
39 questions emerged as the most pressing to be considered:

- 40 • Errors in the boundary conditions for the high resolution model exist due
41 to intrinsic errors in the synoptic scale model and to the process of taking
42 the coarse data down to a fine scale. Should the high resolution data

1 assimilation system be tailored to incorporate these uncertainties in the
2 boundary conditions?

- 3 • A recent study [Baxter et al., 2011] has shown that large scale meteorological
4 features may not be sufficiently well represented in a limited area
5 domain, thus posing difficulties for DA in the smaller domain. What scales
6 should one analyse in high resolution DA (just the small scale or also the
7 large scales)?
- 8 • In a future where NWP uses correlated observation errors, how do the
9 scales implicit in the background and observation error correlations interact?
10

11 The future of observational networks were discussed, specifically the net-
12 works which are not being designed or run specifically for meteorological ap-
13 plications. For example, important meteorological data is being extracted from
14 existing networks such as AMDAR [AMDAR, 2013] and mode-S data [de Haan,
15 2011; de Haan and Stoffelen, 2012; Strajnar, 2012] from air traffic, humidity
16 measurements from global positioning systems [de Haan, 2013] and road traffic
17 data [Mahoney and O’Sullivan, 2013]. Increasingly, cheap sensors found in mo-
18 bile phones are being adapted for use in all kinds of observational networks. If
19 such sensors prove to be the most important part of a meteorological observa-
20 tional network then the agencies which rely on them will come under increasing
21 pressure to control them in order to have confidence in their resilience.

- 22 • How will operational centres ensure the security of new ad-hoc networks
23 of observations?

24 Making full use of all of the available meteorological observations will still be
25 limited by the amount of computational power available to operational centres.
26 In the next generation of data assimilation systems more value may be gained
27 by incorporating information such as error structures in observations [Stewart
28 et al., 2008, 2013b; Weston, 2011; Stewart et al., 2013a; Bormann and Bauer,
29 2010] instead of simply increasing the number of observations.

- 30 • What gains could be made in forecasting by including observational error
31 structures in the data assimilation process compared with simply increas-
32 ing the number of observations?

33 In order to seek the greatest improvement of forecast skill in all applications
34 of atmospheric science, data assimilation must be heavily invested in. Only in
35 doing so will the gap between modern models of atmospheric dynamics and high
36 resolution observations be bridged in a rigorous way. Whilst the use of devel-
37 opment systems or *test-beds* were strongly encouraged a decade ago [Dabberdt
38 et al., 2005], the ability for researchers to test their advances using operational
39 systems and access any impact of new types of observations remains rather
40 limited. Systems like the Data Assimilation Research Testbed (DART) [Ander-
41 son et al., 2009], OpenDA [OpenDA, 2013] and the Parallel Data Assimilation

1 Framework (PDAF) [Nerger and Hiller, 2012] have the ability to test well de-
2 veloped DA methods on new models in various areas of science, but they do
3 not easily lend themselves to testing novel DA methods with operational at-
4 mospheric science models. Adoption of functionality such as EMPIRE [Browne
5 and Wilson, 2014] in operational forecast models would allow rapid testing and
6 prototyping of academic concepts and theories in the most realistic settings.

7 The need for a flexible data assimilation system that can be accessed by
8 researchers in academia and industry who are not in the operational centres
9 remains an imperative goal that if created will benefit the whole atmospheric
10 science community.

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